Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects

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Abstract

Purpose – The main purpose of our study is to analyze the influence of Artificial Intelligence (AI) on firm performance, notably by building on the business value of AI-based transformation projects. This study was conducted using a four-step sequential approach: (1) analysis of AI and AI concepts/technologies; (2) in-depth exploration of case studies from a great number of industrial sectors; (3) data collection from the databases (websites) of AI-based solution providers; and (4) a review of AI literature to identify their impact on the performance of organizations while highlighting the business value of AI-enabled projects transformation within organizations.

Design/methodology/approach – This study has called on the theory of IT capabilities to seize the influence of AI business value on firm performance (at the organizational and process levels). The research process (responding to the research question, making discussions, interpretations and comparisons, and formulating recommendations) was based on a review of 500 case studies from IBM, AWS, Cloudera, Nvidia, Conversica, Universal Robots websites, etc. Studying the influence of AI on the performance of organizations, and more specifically, of the business value of such organizations' AI-enabled transformation projects, required us to make an archival data analysis following the three steps, namely the conceptual phase, the refinement and development phase, and the assessment phase.

Findings – AI covers a wide range of technologies, including machine translation, chatbots and self-learning algorithms, all of which can allow individuals to better understand their environment and act accordingly. Organizations have been adopting AI technological innovations with a view to adapting to or disrupting their ecosystem while developing and optimizing their strategic and competitive advantages. AI fully expresses its potential through its ability to optimize existing processes and improve automation, information and transformation effects, but also to detect, predict and interact with humans. Thus, the results of our study have highlighted such AI benefits in organizations, and more specifically, its ability to improve on performance at both the organizational (financial, marketing and administrative) and process levels. By building on these AI attributes, organizations can, therefore, enhance the business value of their transformed projects. The same results also showed that organizations achieve performance through AI capabilities only when they use their features/technologies to reconfigure their processes.

Research limitations/implications – AI obviously influences the way businesses are done today. Therefore, practitioners and researchers need to consider AI as a valuable support or even a pilot for a new business model. For the purpose of our study, we adopted a research framework geared toward a more inclusive and comprehensive approach so as to better account for the intangible benefits of AI within organizations. In terms of interest, this study nurtures a scientific interest, which aims at proposing a model for analyzing the influence of AI on the performance of organizations, and at the same time, filling the associated gap in the literature. As for the managerial interest, our study aims to provide managers with elements to be reconfigured or added in order to take advantage of the full benefits of AI, and therefore improve organizations' performance, the profitability of their investments in AI transformation projects, and some competitive

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advantage. This study also allows managers to consider AI not as a single technology but as a set/combination of several different configurations of IT in the various company's business areas because multiple key elements must be brought together to ensure the success of AI: data, talent mix, domain knowledge, key decisions, external partnerships and scalable infrastructure.

Originality/value – This article analyses case studies on the reuse of secondary data from AI deployment reports in organizations. The transformation of projects based on the use of AI focuses mainly on business process innovations and indirectly on those occurring at the organizational level. Thus, 500 case studies are being examined to provide significant and tangible evidence about the business value of AI-based projects and the impact of AI on firm performance. More specifically, this article, through these case studies, exposes the influence of AI at both the organizational and process performance levels, while considering it not as a single technology but as a set/combination of the several different configurations of IT in various industries.

Keywords Artificial intelligence, Cases studies, Business value, Process innovation, Firm performance

Paper type Research paper

1. Introduction

Information technologies (ITs) have become ubiquitous in professional activities, disrupting and affecting all core processes and operations (Devaraj and Kohli, 2003; Nwamen, 2006). When integrated with the ecosystem of businesses, IT can produce visible impacts, especially on the relationship between the company and its customers, prospects, and partners (Lauterbach, 2019; Nwamen, 2006). They also play a key role in the way companies' processes and operations will evolve. Today, AI remains the most spectacular IT application, a technology that has gone through an unequaled development over the last decades (Blanchet, 2016; Lee *et al.*, 2018; Wiljer and Hakim, 2019). It is defined as a set of "*theories and techniques used to create machines capable of simulating intelligence. AI is a general term that involves the use of a computer to model intelligent behavior with minimal human intervention*" (Benko and Lányi, 2009; Haenlein and Kaplan, 2019; McCorduck *et al.*, 1977). IDC estimates that 40% of digital transformation initiatives in 2019 will use AI services and that 75% of business applications will use AI by 2021 (Crews, 2019). To improve productivity and develop new services, organizations will have to rely even more on AI to improve their performance (CIGREF, 2016, 2018; Crews, 2019). Since the early 2010s, the American GAFAM or the Chinese BATX, among many others, have embarked on a frantic race for AI, focusing on its most promising component which is the "Learning Systems" (Machine Learning or Deep Learning) (Lee *et al.*, 2018; Pwc, 2019; Vochozka *et al.*, 2018). However, the benefits and immense possibilities offered by AI make it a market of the future par excellence (Pwc, 2018, 2019; Tractica, 2018). The digital revolution has already produced its effects by transforming the world into a modern one characterized by the supremacy of data in every business activity Data is no longer confined to data centers. With sensors of any kind, any object or environment of objects is henceforth capable of measuring and producing data (Dopico *et al.*, 2016; Lee *et al.*, 2018; Sheth, 2016). Industrial and digital (information) revolutions have undoubtedly had a financial impact on virtually every aspect of our society, life, business, and employment (Blanchet, 2016; Yoav Shoham, 2018). Will the next AI revolution produce similar and far-reaching effects on the business value of organizations? Our study proposes to analyze the effects of AI capabilities on improving performance at the organizational level and their intermediate effects on improving process-level performance. This analysis will be particularly concerned with the business value of AI-enabled transformation projects in organizations.

Although still far from equaling "Human Intelligence" as a whole and its complexity, AI is extremely effective in carrying out specific tasks, and its impact on the world and organizations is undoubtedly considerable (Blanchet, 2016; Lee *et al.*, 2018; Wiljer and Hakim, 2019; Zhong, 2008). Therefore, the objective of this study is to fill this gap by answering the following research questions: *Do AI capabilities influence performance improvement at both* *the organizational and process level? What is the business value of AI-based transformation projects within organizations?*

For answering these questions, our study drew on two main data sources: (1) the existing literature on organizational transformation enabled by ITs, including specifically AI and related sub-technologies such as Machine Learning, Deep Learning, Chatbots, Neuronal Network, and (2) a series of mini-cases that were analyzed and retrieved from sources such as the archives of AI solution providers and a leading professional journal on the influence, adoption and use of AI technologies in various sectors.

The rest of this document is structured as follows: section 3 discusses the proposed model, while section 4 presents the research methodology based on the case studies. Section 5 is devoted to the verification and validation of our proposals based on the qualitative analysis of the selected mini-case studies, followed by a presentation of the results, the main conclusions of which are discussed in section 6. Section 7 includes the limitations, research implications and directions for future research. Section 8 serves as a conclusion.

2. Literature review

2.1 Artificial intelligence and its evolution over time

From the very beginning of computer science, researchers like Alan Turing considered the possibility for a computer to play chess, as a test of the machine's intelligence. Thus, he published "Intelligent Machinery" in 1948 and "Computing Machinery and Intelligence" in 1950, both of which will inspire future scientific research in AI (Turing, 2009). Literally, AI means the use of technological devices aimed at reproducing the cognitive abilities of humans to achieve objectives autonomously, taking into account any constraints that may be encountered (Benko and Lányi, 2009; Haenlein and Kaplan, 2019; McCorduck *et al.*, 1977). Table 1 describes some of the works that have contributed to the creation of AI and its evolution over time.

2.2 Artificial intelligence and business activities

Since 2010, however, AI has been booming again, mainly due to considerable improvements in the computing power of computers and the access to massive amounts of data (CIGREF, 2018; Pwc, 2019). This rebirth of AI is the consequence of three (03) breakthroughs: (1) the introduction of a much more sophisticated class of algorithms; (2) the arrival on the market of low-cost graphics processors capable of performing large amounts of calculations in a few milliseconds; and (3) the availability of very large, correctly annotated databases allowing for more sophisticated learning of intelligent systems (Jain *et al.*, 2004; Khashman, 2009; Pwc, 2019).

AI and its technologies (machine learning, deep learning, chatbot, neural network, virtual assistant and others) are fundamentally reshaping the business and organizational processes of companies (CIGREF, 2018; Kuzey *et al.*, 2014; Pwc, 2019). In fact, AI has already transformed the overall structure of organizations and the relation with their environment. AI has driven a new way of managing information, and this represents both a challenge and an immense opportunity for organizations; but seizing this opportunity requires a change in culture, mentality and skills (Di Francescomarino and Maggi, 2020; Lee *et al.*, 2018; Sikdar, 2018). For example, IBM offers Watson solution (named after Thomas Watson [1913–1994], former IBM manager), which is an AI computer program designed to answer natural language questions in a variety of real-world activities (marketing, management, justice, healthcare) (Kohn *et al.*, 2014). One of its applications is the Watson Health service, which offers physicians the opportunity to jointly use current medical data and their patient data to personalize patient care, including the pros and cons of a patient (Kohn *et al.*, 2014).

Date	Authors' contribution to the development of AI
1940–1956	(1) Wiener develops cybernetics, the science of how the human mind works, with the aim of modeling the mind as a "*black box*" with behavior dependent on feedback mechanisms. But this approach postulates that the brain and the architecture of its hundreds of billions of cells are mathematically mobilizable. This approach was further sublimated by the work of *Donald Hebb*, who is helping to endow formal neurons with learning capacities Brown and Milner, (2003) (2) McCulloch and Pitts invented in 1943 the first mathematical model of the biological neuron, the formal neuron, using a physiological approach to AI Benko and Lányi (2009); Haenlein and Kaplan (2019); McCorduck *et al.* (1977) (3) Herbert Simon introduced the notion of limited rationality in 1947. Later, in 1945, Allen Newell introduced the notion of heuristics for problem solving; an empirical method of problem solving, whose validity or efficiency is not proven. Their work also illustrates the cross-fertilization between computer science and AI. First, the development of computer science makes it possible to conduct AI experiments; and second, the problems posed by AI experiments lead to the production of tools that serve the development of computer science Benko and Lányi (2009); Haenlein and Kaplan (2019); McCorduck *et al.* (1977) (4) Between 1937 and 1948, Shannon established the link between Boolean algebra and electrical circuits and thus designed the digital electronics and information theory Verdu (1998) (5) Nathaniel Rochester developed the first symbolic assembler language. He then occasionally contributed to several AI projects (development of the LISP language, the Geometry Theorem Prover and the first symbolic assembler language) Gelernter *et al.* (1958); Rochester *et al.* (1956) (6) In 1949, Donald Hebb invented the rule that allows formal neurons to be equipped with learning abilities. Thus, this principle, which explains that memory is to be formalized as a feedback process in formal neural networks, makes it possible to establish a link between thought and language Benko and Lányi (2009); Haenlein and Kaplan (2019); McCorduck *et al.* (1977) (7) John McCarthy took a logic approach for building a thinking machine Kline (2010); McCarthy (1989) (8) Marvin Minsky took a schematic approach for building an artificial neural network Minsky (2007); Minsky and Papert (1972) (9) In 1954, a first program written at Georgetown University made it possible to translate several dozen simple sentences. The program uses 250 words and only six grammar rules and runs on an IBM 701 Hutchins (2004) (10) Von Neumann's work on the architecture of a calculator and Turing's work on the theorization of calculable functions by machines Benko and Lányi (2009); Godfrey and Hendry (1993); Haenlein and Kaplan (2019); McCorduck *et al.* (1977) (11) In 1956 Newel, Simon and Shaw developed the Information Processing Language (IPL), with list structures, allowing the manipulation of chained elements to reproduce the associative character of human memory Benko and Lányi (2009); Haenlein and Kaplan (2019); McCorduck *et al.* (1977) (12) We also note the contribution of the work of several researchers such as *Ray Solomonoff* on machine learning and the invention of the concept of algorithmic probability Solomonoff (1997); and *Oliver Selfridge*, a precursor of expert systems, thanks for his work on pattern recognition Husbands *et al.* (2008) (13) The notion of AI has existed in the literature for a long time, particularly in films and television series, but its scientific origin is said to have first appeared in *1956*, at a conference organized by McCarthy at Dartmouth College (USA) McCarthy *et al.* (2006)

(*continued*)

Table 1.
Evolution of AI through time

Date	Authors' contribution to the development of AI
1956–1974	(1) The golden age of AI, with a lot of public funding injected for AI research Buchanan (2005) (2) The development of MYCIN, the first expert system in charge of identifying bacteria responsible for serious infections and recommending the right antibiotics Shortliffe *et al.* (1975)
1974–1980	(1) Over-ambitious expectations combined with limited means lead to the first "winter" of AI Benko and Lányi (2009); Godfrey and Hendry (1993); Haenlein and Kaplan (2019); McCorduck *et al.* (1977)
1980–1987	(1) The emergence of intelligent systems between 1980 and 1987 gave rise to a new surge of enthusiasm and determination in the development of AI. Kai-Fu Lee and Sanjoy Mahajan developed BILL, a Bayesian learning system for playing the board game Othello Benko and Lányi (2009); Godfrey and Hendry (1993); Haenlein and Kaplan (2019); McCorduck *et al.* (1977)
1987–1993	(1) The sudden collapse of the specialized hardware industry led to a second AI "winter" Benko and Lányi (2009); Haenlein and Kaplan (2019); McCorduck *et al.* (1977); Wamba *et al.* (2017)
1993–2011	(1) AI becomes data-driven, computer power increases Buchanan (2005). Thus in 1997, IBM's DeepBlue system defeated chess champion Gary Kasparov Campbell *et al.* (2002). The increase in the amount of data available, the growth of connectivity and the increased computing power of electronic devices allowed for further advances and led to a sharp rise in the number of patent applications related to AI as from 2012 Yoav Shoham (2018)

Table 1.

Advances in AI research have made it an inescapable topic of trends in the current decade. Announced since the 1960s, AI has made important progress that was eventually confirmed since the 2000s with the emergence of "Machine Learning" (automatic learning: machines 'learn' from the datasets offered to them), whose latest development is "Deep Learning" (which relies on neural networks) (Buchanan, 2005; Pwc, 2019; Yoav Shoham, 2018). Indeed, machine learning algorithms are used to train the deep layers of neural networks. Rather than modeling vast amounts of information (e.g. calculating all the possible moves in a chess game or replacing images in videos), neural networks learn by digesting millions of test data (medical diagnostics and efficacy of new drugs, estimates of energy reserves, price forecasts) (Pwc, 2019; Zemouri *et al.*, 2019). Combined with big data, these types of AI perform operations and actions that exceed human actions in terms of speed and relevance. Many sectors and services are already or will soon be affected by these technological innovations; they include transport with autonomous vehicles (Falcone *et al.*, 2007), health with disease detection programs (cancers and other diseases) through Machine Learning and Deep Learning (Jiang *et al.*, 2017; Koh and Tan, 2011), customer relationship with the use of conversational agents (Rubin Victoria, Chen and Thorimbert Lynne, 2010), natural processing language and automatic email processing by virtual robots (Gabrilovich and Markovitch, 2009), security with facial recognition and artificial vision technologies, and urbanism with a smart city (Jain *et al.*, 2004; Khashman, 2009; Srivastava *et al.*, 2017). Given its many benefits in terms of innovation and prowess, AI can be deployed across the entire value chain of the organization, integrating virtually all aspects: research and development, maintenance, operation, sales and marketing, planning and production, demand forecasting and services (Kuzey *et al.*, 2014; Pwc, 2019).

Viewed as a key growth factor, AI can allow any organization to achieve the following: (1) increase the efficiency of operations, maintenance and supply chain operations, optimize and improve the customer experience, improve products and services (with new features), as well as item recommendation processes (retail and other industries) (Kuzey *et al.*, 2014; Pwc, 2019);

(2) improve rapid and automatic adaptation to changing market conditions, create new business models, optimize the relationship between supplies and needs with better forecasting and planning capacity (Kuzey *et al.*, 2014; Pwc, 2019); (3) detect fraud (banking and other sectors), automate threat intelligence and information systems, automate IT function (IT system and processes) and optimize sales processes (CIGREF, 2018; Pwc, 2019); (4) diagnose and treat pathologies (Koh and Tan), anticipate a disease and its evolution, promote the recommendation of personalized treatments, assist in decision-making by advising on the diagnosis, prevent by anticipating epidemics and acting on pharmaceutical vigilance (Jiang *et al.*, 2017; Johnson *et al.*, 2018); and (5) automate quality management investigation and recommendation, manage supply, logistics and fleet assets (logistics/transport and most industries) (Di Francescomarino and Maggi, 2020; Rubin Victoria *et al.*, 2010; Sikdar, 2018). Tractica's data on market trends are unquestionable with these statistics: AI should generate nearly $90 billion in profits by 2025, as compared to only $7 billion in 2018. North America, Europe and Asia–Pacific will remain the main beneficiaries of the benefits of AI and its multiple technologies (Tractica, 2018). In fact, three segments of AI will be the most promising by 2025: (1) detection, identification and avoidance of moving objects, (2) static image recognition, classification and marking, and (3) medical patient data processing. These sectors could generate a cumulative turnover of nearly twenty-one (21) billion euros between 2016 and 2025 (Tractica, 2018).

2.3 IT capabilities

In a context of globalization and internationalization of markets, innovation, product/service quality and customer requirements have led companies to integrate IT into their managerial approach (Bolwijn *et al.*, 2018; Rachinger *et al.*, 2019; Stank *et al.*, 2019). This evolution of the economic environment results in competitiveness requirements, which imply a modernization of the information device of organizations. Organizations have always aspired to assign more tasks to machines in order to reduce costs and improve efficiency. It all started with assembly lines, which replaced human labor in mechanical and repetitive tasks previously known as "manual labor" (Dopico *et al.*, 2016; Lee *et al.*, 2018).

Nowadays, the challenge for 21st-century organizations lies in their ability to innovate in the face of an extremely dynamic market in which competitive positions are constantly evolving (Stank *et al.*, 2019). The globalization of the economy brings more and more competition and more information to be compiled to meet the challenge (Queiroz Maciel, Pereira Susana Carla, Telles and Machado Marcio, 2019; Rachinger *et al.*, 2019; Stank *et al.*, 2019). But, in a world where information is a strategic asset (the key to value creation), it is clear that the organization's ability to manage this information is crucial to its competitiveness (is of strategic importance) (Kuusisto, 2017; Rachinger *et al.*, 2019). Innovative IT is fundamentally reshaping organizations' business and organizational processes. They have already changed the overall relationship between IT and the rest of the organization. This new way of managing information has become both a challenge and a tremendous opportunity for organizations, but seizing this opportunity requires a "change in culture, mindset, and skills" (Devaraj and Kohli, 2003; Nwamen, 2006; Turulja and Bajgoric, 2018). Furthermore, AI innovations continue to contribute to the benefits of IT in organizations. AI, as part of an organization's ecosystem, can have an impact, particularly on performance, on the relationships between organizations and their customers, prospects, and partners (Kelly *et al.*, 2019; Rubin Victoria *et al.*, 2010). AI is an indispensable factor in the evolution of processes, optimization and flexibility of operations in organizations (Kelly *et al.*, 2019; Rubin Victoria *et al.*, 2010). Given the rapid technological advances, particularly in the field of AI, the idea of entrusting more complex tasks to machines no longer seems as far-fetched as it was several years ago. As a set/combination of several different IT configurations and capabilities in different areas of an organization's business, AI has already proven its effectiveness in automating monotonous and repetitive tasks, usually performed by specialists like human resources administrators, salespeople and small contractors (CIGREF, 2018; Pwc, 2019; Rachinger *et al.*, 2019).

It is expected that in the future, organizations and their leaders increasingly deal with an "economy of power" whereby the search for a position on the market will guide any organization's action planning to safeguard its decision autonomy, strategic leeway and increased competitive advantage (Liu *et al.*, 2015; Turulja and Bajgoric, 2018). Such a position implies not only a competitive advantage in the market but also resources that allow the valuation of that advantage. Therefore, researchers, practitioners and organizations are keen to respond to these questions: how do information technologies and their capabilities contribute to improving the performance of organizations (Farhanghi *et al.*, 2013; Ruiz-Mercader *et al.*, 2006; Turulja and Bajgoric, 2018)? How do IT capabilities influence business value improvement in IT-enabled transformation projects in an organization (Abijith and Wamba, 2012; Benner, 2009)?

Since the beginning of the 1980s, researchers and practitioners have pondered seriously on the relationship between investments in information technology (IT) and organizational performance, as well as on a growing development of performance within organizations (Farhanghi *et al.*, 2013; Nwamen, 2006; Ruiz-Mercader *et al.*, 2006). One of the major difficulties in this line of research is to provide accurate, useful and undisputed results. It is true that ITs are particularly pervasive in many professional activities and are profoundly transforming processes and operations at the organizational level, but their impact on the performance of an organization is still under investigation (Chaumon *et al.*, 2018; Ha and Jeong, 2010). Koski (1999) have shown that IT investments have no significant effect on the performance of industries and firms. This was not confirmed by authors such as and Devaraj and Kohli (2003), who rather believe that IT has a positive influence on the performance of organizations. Beyond every approach, some authors, in an effort to clarify the link between organizational performance and information technology capabilities, proposes six (06) theoretical approaches to evaluate the impact of IT on organizational performance: (1) the economic theory-based approach, which is suitable for to finding an economic function for explaining the relationship between IT and performance (Lehr and Lichtenberg, 1999; Lichtenberg, 1995); (2) the social psychology approach, which seeks to explain the effect of IT on performance through their intermediate impacts on individual users and/or groups of individuals in organizations (Davis, 1989; DeLone and McLean, 1992; Delone and McLean, 2003; Zmud, 1979); (3) the competitive analysis approach, which makes an analysis to assess the competitive impact of IT at the industrial, environmental and organizational levels (Devaraj and Kohli, 2003; Farhanghi *et al.*, 2013; Ruiz-Mercader *et al.*, 2006); (4) the strategic alignment approach, which advocates a harmony between the IT strategy and the strategy of the organizations to be able to improve the performance (Henderson and Venkatraman, 1999; Nwamen, 2006; Turulja and Bajgoric, 2018); (5) the evaluation approach based on the processes, whereby the relationship between IT and organizational performance is viewed from the perspective of an added value-creating process for an organization (Mooney *et al.*, 1996; Nwamen, 2006; Turulja and Bajgoric, 2018); and (6) the resource-based evaluation approach, which is based on the assumption that organizations have resources that can allow them to have a privileged competitive position, and therefore, superior performance (Barney *et al.*, 2001; Grant, 1991; Wernerfelt, 1984).

The role of IT in organizational performance is an important subject in the field of information systems research, especially as regards their potential to create value. The resource-based evaluation approach focuses on IT capabilities in the firm—"*the organization's ability to combine its organizational, human and material IT resources to create value for the organization*" (Abijith and Wamba, 2012; Kim *et al.*, 2011). According to these authors, an organization has "valuable" and "scarce" resources that provide them with a competitive advantage, and thus, create business value (Grant, 1991). First, they combined these resources in tangible resources (financial capital, capital assets, physical assets, etc.), intangible resources (reputation, brand name, etc.), and staff-based resources (knowledge, skills, staff know-how, etc.). Second, they suggested three dimensions in relation to the physical, human and organizational aspects of these resources in order to analyze and understand IT capabilities: (1) IT management capabilities; (2) IT personal expertise; and (3) IT infrastructure flexibility(Abijith and Wamba, 2012; Bhatt *et al.*, 2010; Kim *et al.*, 2011).

3. Conceptual model

The design of our research model was done in two (02) steps. First, we conducted a literature review on the impact, the influence of IT on improving performance both at the organizational and process level, while specifically considering works such as those by (Abijith and Wamba, 2012); Kim *et al.* (2011) and Mooney *et al.* (1996). Second, we made a contextual analysis of the collected mini-case studies to highlight the business value of AI-based transformation projects both at the organizational and process levels. Thus, the research model, which highlighted the evidence obtained from these case-studies analyses, is based on six proposals (see Figure 1). This set of proposals allowed the capture of a significant influence of organizational performance and process innovation through AI-based transformation projects.

3.1 AI capabilities (AICAP)

AI capabilities could be defined as the firm's ability to create a bundle of organizational, personnel and AI resources for business value creation and capture (Abijith and Wamba, 2012; Kim *et al.*, 2011; Liu *et al.*, 2013). Prior studies have already used different types of IT categories. There are different types of resources in a company: organizational, human, material and immaterial (Kim *et al.*, 2011; Liu *et al.*, 2013). Based on previous research, we consider three types of AI resources in our study:

AI Management Capability (AIMC), which is the ability of an organization and its staff to administer or to model intelligent behavior in a computer or technology to create added value for the organization's sustainability. AI management capability potential is peculiar to

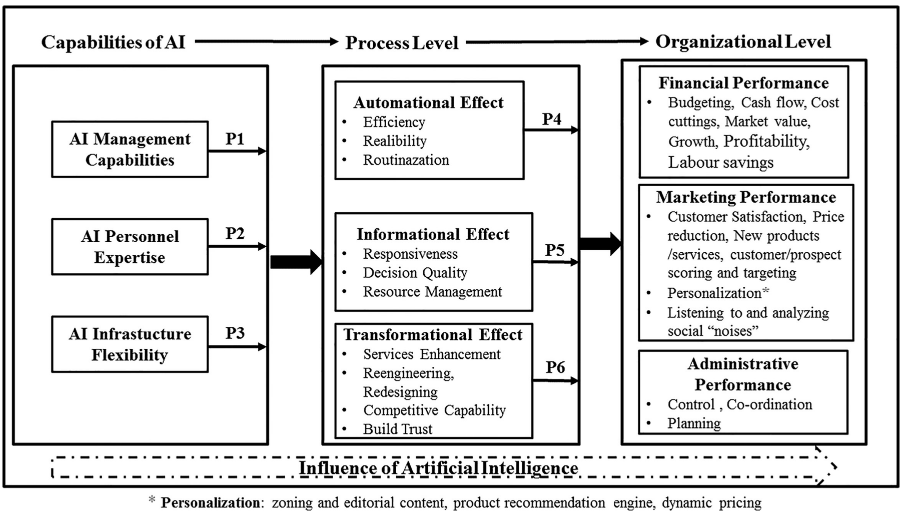

Figure 1.
Research model, Adapted from Anand and Fosso Wamba (2013)

strategic planning, strengthening relationships within and between companies, investment decision-making, coordination and control (Ha and Jeong, 2010; Hamet and Tremblay, 2017; Kim *et al.*, 2011). The potential of AI management capacity is specific to "strategic planning, strengthening relationships within and between organizations, investment decision-making, coordination and control." Kim *et al.* (2011) have demonstrated in its study that control, which depends on the expertise of the staff, has influences on infrastructure flexibility.

Proposition 1. AI management capabilities have a significant positive effect on AI capabilities, which are positively associated with the influence of AI at the process level.

AI personal Expertise (AIPE), which is defined as the professional skills and knowledge of AI-related technologies, business functions and relational (or interpersonal) domains required by the organization's staff for modeling and/or using intelligent behavior in a computer or other technology to accomplish the tasks assigned to it (Ha and Jeong, 2010; Hamet and Tremblay, 2017; Jiang *et al.*, 2017; Kim *et al.*, 2011). It is important for an organization's IT staff to have a combination of skills—awareness, ownership, integration, management of AI technologies—knowledge of IT elements that would allow for more effective management of the AI resources at their disposal. Thus, the creation of business value by organizations depends on the effectiveness of AI strategic alignment with its strategy; and the latter improves if staff have the right combination of skills. However, the expertise of AI staff becomes an intangible asset for organizations when IT staff understands how the organization's strategies are mixed with IT and AI skills (Abijith and Wamba, 2012; Kim *et al.*, 2011; Liu *et al.*, 2013). As a result, organizations with competent AI staff are more likely to meet the requirements of ever-changing dynamic environments by aligning AI with strategies, developing reliable and cost-effective intelligent systems. Therefore, we can enunciate this proposition:

Proposition 2. AI personal expertise has a significant positive effect on AI capabilities, which are positively associated with the influence of AI at the process level.

AI infrastructure Flexibility (*AIIF*), which refers to the composition of all technological assets (software, hardware, and data, etc.), systems and their components, network and telecommunications installations and applications that are necessary for the implementation of an AI system capable of performing tasks (Kim *et al.*, 2011; Liu *et al.*, 2013; Wamba *et al.*, 2017). The flexibility of deploying AI infrastructure for organizational operations allows the organization's staff to rapidly support various system components and adapt to changing business conditions and business strategies, such as economic pressures, strategic alliances, acquisitions, global partnerships or mergers (Abijith and Wamba, 2012; Bhatt *et al.*, 2010; Fink and Neumann, 2009; Kim *et al.*, 2011). Multiple key elements must be brought together to ensure the success of AI in an organization. They include data, combined talent (IT and AI), domain knowledge and technologies, key decisions, external partnerships, and scalable infrastructure. The first four elements represent the fuel and scalable infrastructure, which is the engine without which nothing can work. A better IT infrastructure allows organizations to use IT resources effectively and efficiently so as to support structural restructuring through the deployment of AI technologies. A self-configuring, self-healing and self-optimizing infrastructure will prevent problems before they occur, promote strategic business process innovation, and help to proactively improve performance and optimize available resources (Kim *et al.*, 2011; Liu *et al.*, 2013; Wamba *et al.*, 2017). Therefore, we can formulate this proposition:

Proposition 3. AI infrastructure flexibility has a significant positive effect on AI capabilities, which are positively associated with the influence of AI at the process level.

3.2 Performance improvement at the process level (PIPL)

In organizations, performance improvement at the process level is usually measured using key performance indicators concerned with efficiency, capacity, productivity, quality, profitability, competitiveness, effectiveness, and value (Lebas, 1995; Santos and Brito, 2012). These key process performance indicators are used to monitor the organization's outputs. In other words, they make it possible, through the collection of relevant information, to monitor the evolution or innovation of the process during and after the introduction, adoption and integration of information technology or of a repository of best practices by an organization (Nwamen, 2006). These indicators provide information that allows the manager to make decisions that will improve the efficiency and effectiveness of the process.

It is commonly accepted that ITs are a vector of performance development in a company (Abijith and Wamba, 2012; Kim *et al.*, 2011; Mooney *et al.*, 1996). However, whether their impact on the performance of business processes also evolves remains an open issue and a major concern for the researchers. Yet, the available literature suggests some relevant approaches to evaluate the impact of information technology capabilities on business processes. For instance, Mooney *et al.* (1996) identified three complementary effects, namely the informational, transformational, and transformational effects. Since part of our study focuses on the influence of AI on business processes, the three above-mentioned effects shall be used to analyze this influence.

The automation effect (*AE*) refers to the value-effectiveness perspective derived from the use of informatics to replace the human-based process in the organization (Abijith and Wamba, 2012; Kim *et al.*, 2011; Mooney *et al.*, 1996). The automation effect is demonstrated using AI and its technologies to create reproducible instructions and processes to replace or significantly reduce human interaction. This effect is particularly significant if the introduction of AI is followed by evidence of increased efficiency/reliability through the automation of manual or paper-based processes. This is a financial contribution through labor savings and budget reduction(Abijith and Wamba, 2012; Kim *et al.*, 2011; Liu *et al.*, 2013).

Proposition 4. The automation effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level.

The informational effect (*IE*) refers to the ability of AI to collect, store, process and disseminate information within and between organizations (Abijith and Wamba, 2012; Kim *et al.*, 2011; Mooney *et al.*, 1996). Data as fuel for AI technologies are used by algorithms to produce reliable, fresh, available, complete, relevant, dynamic, transmittable, up-to-date, intelligent and fast information. Thus, the higher the capacity and ability to derive the informational effects of AI and its technologies, the more effectively and quickly the organization can make quality decisions that in turn affect the financial and managerial stability of organizations (Abijith and Wamba, 2012; Kim *et al.*, 2011; Liu *et al.*, 2013; Mooney *et al.*, 1996). Other benefits of the informational effect induced by AI include administrative tasks such as renewed organizational control over resources, enhanced coordination between and within organizations, and rapid staff responsiveness.

Proposition 5. The informational effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level.

The transformational effect (*TE*) refers to the value derived from AI capacity that facilitates and enables innovation and process transformation (Abijith and Wamba, 2012; Kim *et al.*, 2011; Mooney *et al.*, 1996). Given the ability of AI to support innovation and process transformation, we could rely on some superficial analysis coupled with a literature review to consider the transformational effect as an important variable for our research model. It is an essential driver for reengineering and redesigning the existing organizational structure. The transformational effect is composed of variables such as service enhancement, reengineering redesigning, competitive capabilities and build trust. The transformational effects of AI capabilities are materialized through these variables at the process level. Transformation effects play a leading role in improving customer relations and creating new products/services. They are "*closely linked in supporting service transformation through innovation and process redesign*" (Abijith and Wamba, 2012; Kim *et al.*, 2011; Mooney *et al.*, 1996).

Proposition 6. The transformational effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level.

4. Research methodology

This study was conducted following the three phases shown in Figure 2. The starting point was of conceptual nature, the aim of which was to choose the target case studies to be used in this study. This was followed by the refinement and development phase, which was devoted to verifying the reliability of case study information. The final phase (assessment phase) was designed to assess the various case studies and derive some practical and theoretical implications for the IT capability theoretical framework.

We adopted the archival data analysis in this study. The main reason is that in this digital age, secondary data from archived case studies can be more easily collected and rendered available to perform analyses of all kinds. To some extent, this is an attractive avenue for researchers, as it is common to find that initial data collected at high prices are often poorly or not sufficiently exploited. This type of methodology was already used by authors like (Abijith and Wamba, 2012) to analyze the "*Business Value of RFID-Enabled Healthcare Transformation Projects*", or Faure *et al.* (2018) who built on 13 case studies to show "*How different agricultural research models contribute to impacts: Evidence from 13 case studies in developing countries*".

4.1 Conception phase

According to Ponelis (2015) and Ridder (2017), the case studies are characterized by an approach that "*facilitates the exploration of a phenomenon in its context using various data sources (qualitative or quantitative).*" Through case studies, researchers can study the "*properties, actions, attitudes and social structures of individuals, groups or institutions by applying one or more methods, such as well as participant observation, interviews and document analysis*" (Meyer, 2015; Ponelis, 2015). The fact that AI is an innovative and

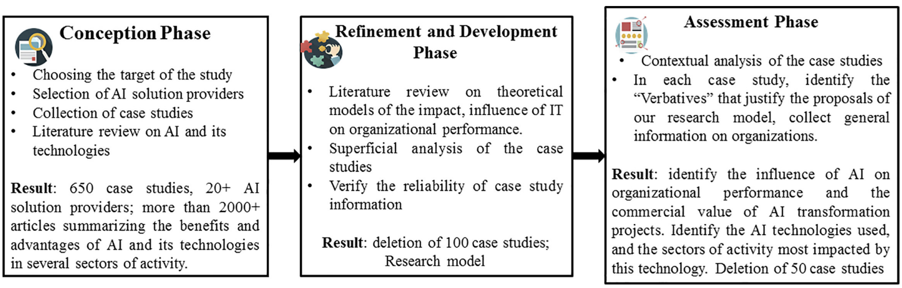

Figure 2.
Methodology process

emerging technology for many industries made it optimal for our study to resort to an archival analysis. In fact, it aims to explore innovation based on AI and its technologies in organizations. As a result, we collected five hundred (500) mini-case studies published by approved and world-renowned AI solution providers in their different websites (Appendix 3, Table A3). Such AI players can be divided into five expert groups: IT companies, consulting firms, expert reviews and magazines, research institutions, and IT industry analysts (Di Francescomarino and Maggi, 2020; Rubin Victoria *et al.*, 2010; Sikdar, 2018). The literature review also helped us to determine AI areas and axes with most innovations or those benefiting from the major AI innovations and related technologies. More than 2,000 articles summarizing the advantages and benefits of AI and associated technologies/applications in several sectors were selected. The scientific search engine Google Scholar was the main searching tool used, in which the following key search words were introduced: "influence of artificial intelligence"; "benefits of artificial intelligence"; "business value of artificial intelligence"; "role of artificial intelligence"; "technologies of artificial intelligence"; "types of artificial intelligence"; "artificial in practice". The retrieved mini-case studies provided the raw materials that further underwent some analysis. We added the plug-in "Save as PDF" to the Mozilla Firefox browser (Firefox Quantum, version 67.0b18 64 bits) to facilitate the download of reliable, up-to-date and complete case studies.

4.2 Refinement and development phase

Studying the relationship between IT and organizational performance remains topical, although it has evolved over the years. Today, with the spectacular innovations that AI has brought in its wake, some authors generally combine several theories and models for studying the influence of AI on organizational performance and identifying the business value of transformation projects enabled by the same. A review of the literature enabled us to select suitable theoretical foundations. They included *Paradox Productivity* (Kijek and Kijek, 2019; Polák, 2017; Triplett, 1999), *Process-Oriented Perspective* (Mooney *et al.*, 1996), *Resource-Based View* (Barney *et al.*, 2001; Grant, 1991), and *Dynamics Capabilities* (Kim *et al.*, 2011). Then, the elements provided by these theories could be complemented by information from a preliminary analysis of the selected case studies in order to build a robust conceptual research model.

To ensure the quality, credibility and secondary data contained in the mini-case studies, we ensured whether they contained verifiable facts such as (1) the contact details of the

Table 2. Summary of the proposition/hypothesis results

No	Proposition	Results	Number of case study
P1	*AI management capabilities have a significant positive effect on AI capabilities, which are positively associated with the impact of AI at the process level*	Supported	425
P2	*AI personal expertise has a significant positive effect on AI capabilities, which are positively associated with the influence of AI at the process level*	Supported	173
P3	*AI infrastructure flexibility has a significant positive effect on AI capabilities, which are positively associated with the influence of AI at the process level*	Supported	179
P4	*The automational effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level*	Supported	397
P5	*The informational effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level*	Supported	455
P6	*The transformational effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level*	Supported	426

organizations concerned, (2) the contact details, responsibilities and positions held by organizations' members involved in the case studies, and (3) some extracts from interviews with those actors. For some case studies, we visited the websites of organizations that had integrated AI into their business processes to verify the level of collaboration between them and their suppliers. We also contacted members of these organizations using the emails provided on the case studies. Before including a case study in our sample, we first verified whether the issue at stake was clearly identified or studied. For each case study, it was necessary to know the context, the problem or challenge, the actors involved in the transformation process, the results obtained and the relationship with our problem. So, we tried to answer questions, such as, are the case studies comparable? Are the questions asked relevant? Is the data raw or analyzed?

At the end of this phase, we obtained a list of case studies with topics revolving around: the "*use AI to solve customer queries in seconds, used intelligent workflows to build better experiences for insurance customers; delivers smart marketing that responds to real-time customer behavior with AI systems; use of AI in predictive maintenance of equipment and machinery in organizations; AI combined with image and video recognition in the security industry; personalized financial planning; fraud detection and anti-money laundering; transaction automation in banking and insurance; personalized design and production; customer data generation; automated inventory and delivery management; media archiving and research; content creation (music, marketing, film); and the creation of new content (e.g. movies, music, marketing materials, etc.); custom marketing and advertising; supply chain and production optimization; manufacturing on-demand; trucks and self-delivery; traffic control and congestion reduction; enhanced security; data-driven diagnostic support; pandemic identification; imaging diagnostics (radiology, pathology)*".

4.3 Assessment phase

Finally, we conducted an in-depth analysis of the various mini-case studies to answer our main research question—identify the influence of AI on organizational performance, and more specifically, highlight the business value of AI transformation projects in organizations. This method is appropriate for identifying and studying the meaning of selected themes, oppositions or associations of concepts, the direction of the text (positive, negative or ambivalent), the actors involved, their opinions, beliefs and positions as conveyed by the case studies. For each case studies identified, we identified the verbatim—which refers to the research constructs that are sorted out to support and justify our research proposals. Subjectivity was avoided in the analysis by making a unanimous selection of case studies during the refinement and development phase. Besides, each author of this study carried out a detailed independent analysis of each case study. At the end of the process, evidence that was found by each of us to justify the constructs and proposals of our model was gathered, compared with other data and analyzed with a view to the final results. Ambiguous results obtained by the authors were rejected and simply removed from our sample. Thus, the 500 case studies that were selected after contextual analyses were deemed accurate in terms of facts and results.

5. Analysis of excerpts from sampled case studies

A case study usually consists of several parts, including (1) the context, which answers the questions: "who"? What is the client's field of work? What is the client's history? Who are the organization's members in charge of reporting comments in the case study? For the purpose of our study, this section highlights the capabilities of AI. *The problem* posed is the challenge faced by the customer encountered and how he/she was able to meet it thanks to the AI supplier. Here is described the major challenge, the situation that the company has faced and how it coped with using AI capabilities; (2) the *answer* to the question: "what was the solution proposed by the supplier to the customers?" The point here is to ensure that the customer's perspective is always considered, together with the perception angle of his profits, and the added value he can now benefit from thanks to the supplier's intervention. This section also highlights the business value of AI for organizations; (3) The *results obtained*, which should be the concrete and tangible results obtained by the client. They account for the quantified, quantifiable, measurable and striking data that are being recorded: x% increase in turnover, x customers have gained more each month, etc. All the figures/elements that prove that the supplier's action has been beneficial for the customer should be highlighted. In addition, it is necessary to show all evidence of the influence of AI on performance improvement at the organizational and process levels, as well as the business value of AI-oriented transformation projects. A section like this one is generally part of the case studies that were selected for our research work, and it is often subdivided into several sub-sections. The various case studies developed below show how AI or its technologies/ applications bring value and business value to organizations.

5.1 Case study 1: Abu Dhabi national oil company (ADNOC)

Presentation of the Company: Abu Dhabi National Oil Company (ADNOC) is a major diversified group of energy and petrochemical companies in Abu Dhabi. It belongs to the Chemicals and Petroleum sector. The company has adopted AI, which is based on IBM technology, in order to ensure the automation of its different operations and processes, including for analyzing and categorizing rock samples, speeding the development of digital geological models of reservoirs.

Business Challenge: Determining the hydrocarbon storage capacity and the production characteristics of carbonate rock samples requires time and technical expertise. ADNOC wanted to speed the process without sacrificing accuracy.

Transformation: ADNOC and IBM are relying on cutting-edge AI to develop an automated process for analyzing and categorizing rock samples, and speeding the development of digital geological models of reservoirs.

Business Challenge Story - A Time-Consuming Process: As the largest of seven Emirates in the United Arab Emirates (UAE) in both area and population, Abu Dhabi is one of the world's richest sources of hydrocarbons. Nearly nine percent of the world's known oil reserves and five percent of its natural gas reserves lie within carbonate rocks deep below Abu Dhabi's deserts and waters. ADNOC is one of the world's largest producers of oil and gas. It recognizes the value of incorporating AI into its business processes to optimize operations, enhance recovery and improve decision-making. ADNOC is leading the adoption of AI by streamlining the way it studies Abu Dhabi's hydrocarbon reservoirs. Oil producers like ADNOC seek to maximize oil recovery efficiency by using the fewest wells, the least amount of water and the lowest expenditure. Working toward this goal, engineers construct digital reservoir simulation models to test reservoir behavior, including storage space (porosity), the ability to flow (permeability) and the amount of oil (potential recovery). The models allow engineers to consider different development characteristics, including well spacing, the type of well, the number of wells and pressure maintenance schemes. The foundation of a reservoir simulator's predictive accuracy—used to guide management's multibillion-dollar field development decisions—is the fidelity of the geological model. Geology relies on visual microscopic rock descriptions obtained by means of an optical microscope in a slow, labor-intensive process that has barely changed since the birth of modern geology in 1793. Furthermore, when a petrographer with decades of experience retires, ADNOC loses that person's accumulated experience. And with so many fast-paced, highly technical careers to choose from, few young people are choosing to become petrographers. For these reasons, ADNOC sought a way to preserve its experts' experience and enhance the process, possibly within a machine.

"*By developing an innovation partnership with IBM Watson, we are ensuring that the level of description and interpretation remains at the expert level.*" —Douglas Boyd, Technical Center Petrophysicist, Abu Dhabi National Oil Company.

Transformation story - A Fundamental Shift in How Science Gets Done: For the past several years, IBM has focused on Industry 4.0 initiatives in the oil, gas and petrochemicals industry in the Middle East, leading on digital transformation programs. Partnering with national oil companies in the region is a top priority as IBM works to deliver value through pragmatic partnerships that center on AI, machine learning, the industrial Internet of Things (IoT), cybersecurity and blockchain. At the same time, Hani Nehaid, ADNOC's Geoscience Team Leader, and his team were considering using AI to augment and accelerate the thin section description process. So, when Nehaid along with Douglas Boyd, Technical Center Petrophysicist and Hesham Shebl, Technical Center Geologist (Petrographer), encountered an IBM representative at an industry dinner, the potential of utilizing AI and Watson™ solutions to address this challenge with visual recognition technology became a subject of mutual interest. Boyd explains: "*We had a short discussion with the IBM rep about how we could pursue this aspiration. We started by working together with their data scientists to repeatedly train the platform. Then we prepared a small sample set for them to analyze as a proof of concept. This delivered very accurate results, equivalent to our most experienced petrographer. We were very impressed, and we moved ahead from there.*" In this case, an IBM team comprising representatives from IBM Industry, IBM Services and IBM Cloud divisions worked with ADNOC to begin the first phase of a multi-phase project. Together, they moved from simple to increasingly difficult tasks, employing AI-driven elements of cognitive image recognition, natural language processing and regression. The team spent four weeks training the Watson Visual Recognition service to label two-dimensional (2-D) rock images according to their visual characteristics. As the project continues, the team plans to train the Watson solution to extract additional information from the images. Shebl explains:

> We want to greatly expand the rock image thin section data we capture from Abu Dhabi's subsurface. Many of the management and development decisions we make are based on the properties and interpretations our petrographers make. The more data points we can use, the better and more efficient our models, our development plans and our ultimate hydrocarbon recovery will be. This is fundamental to the success of our industry. [. . .] The more data points we can use, the better and more efficient our models, our development plans and our ultimate hydrocarbon recovery will be. This is fundamental to the success of our industry. —Hesham Shebl, Technical Center Geologist (Petrographer), Abu Dhabi National Oil Company.

Results Story - Radical Increases in Speed and Accuracy: ADNOC's use of AI to augment geological research has already been successful. Although drilling and scanning rock samples must remain manual processes, image classification is now much faster and more automated. Because Watson can analyze 527 images per second, analyzing all the samples taken from a single reservoir now takes only minutes – not months. Beyond the increase in classification speed, Nehaid and his team are already experiencing several other key advantages of the AI-driven Watson solution. With analysis time reduced significantly, ADNOC can evaluate many more rock samples from many more wells, generating more deterministic data. This, in turn, leads to more accurate and effective subsurface models. The solution also improves consistency. Nehaid says:

> Two different geologists with different levels of experience will provide different levels of accuracy in their rock descriptions. With IBM Watson, we are ensuring that the description and interpretation is always at the expert level and that it will remain consistent throughout the years.

"*These factors are enhancing our subsurface models, which in turn significantly de-risk and support better investment decisions in multibillion-dollar field developments*," he adds.

Watson's AI libraries provide ADNOC with a way to preserve its petrographers' decades of experience without having to undergo the years-long process of bringing new experts up to speed. Nehaid asserts:

> The solution lets us free up our geologists' time to focus on model generation, as well as transfer our experts' knowledge and experience to the machine so we can take advantage of their experience after they move on.

Nehaid and his team are optimistic about the future of the project. In this regard, Shebl declares:

> Ultimately, I see machine learning assisting the entire process of creating representative geological models and helping us create a clear understanding of the subsurface. Cutting-edge technology and innovation partnerships are allowing us to create development plans that help us achieve our strategic goals: to increase recovery at the end of a field's life to 70%, and ultimately to help create a more profitable ADNOC upstream.

IBM, too, is encouraged by the success of the ADNOC engagement. Talal Malas, Cognitive and Analytics Practice Leader with IBM Middle East and Africa, explains: "We believe that AI is a partnership between man and machine. This initiative with ADNOC is one of the most exciting use cases in the chemicals and petroleum industry—cognitive geology, which emulates geologists and petrophysicists in classifying rock samples with high accuracy at an enormous scale. It is the perfect example of how AI boosts productivity and frees up highly skilled experts for higher value activities." Ahya Mahmoud, Industry Leader for Industrial Products and Chemicals and Petroleum Industry for IBM Middle East and Africa, adds:

> At IBM we believe in innovation that matters, for our company and for the world. We dare to create original ideas with focus and dedication to our clients' success. The partnership between ADNOC and IBM brought these values to life. The entire value chain builds up from the geosciences, it was intuitive to start there. We share ADNOC's aspiration of further developing the solution to tap into more data points from the subsurface to enhance hydrocarbon recovery.

This case study highlights the benefits of AI's capabilities in the chemicals and petroleum products sector. It should be noted that the IBM ADNOC solution has not only solved the problem of analyzing rocks in the depths of the Earth by helping them optimize their development plans in the field. But it will certainly generate huge future financial gains for the organization. This case study highlights the fact that AI/IT managers in organizations must intervene in AI capabilities to improve organizational performance and create added value, including having a positive impact on AI management capabilities. AI has enabled this organization to increase the speed of delivery and consistency of descriptions of reservoir rock samples (transformational effect, informational effect), accelerate the construction of models to reduce the risk of multi-billion dollar reservoir development decisions (transformational effect, financial performance) and preserve the expertise that petrographers have spent decades developing (administrative performance). This case study provides further evidence to support the P1, P3, P2, P2, P5 and P6 propositions of our research model.

5.2 Case study 377: hospital uses natural language processing for assisted physician documentation

Presentation of the Company: United Healthcare Services (UHS), which operates in the healthcare industry sector, is a regional not-for-profit network of hospitals in the state of New York, USA Its AI application, which is provided by Nuance Communication, is concerned with Healthcare Data Management, and Physician Documentation. Nuance Communication is specialized in natural language understanding, reasoning, and systems integration solutions.

Problem: UHS operates on a value-based healthcare system, meaning its healthcare providers are paid based on the quality of care rather than on the quantity. Here, the quality of healthcare is mainly determined by physician documentation, which is a set of progress notes that contain patient clinical status, such as improvements or declines in patients' health.

Most of UHS's physicians are independent practitioners, which made it a challenge for UHS to streamline the adoption of documentation best practices across its network. Besides, physicians spent several manual hours documenting patients' progress. Therefore, UHS wanted to provide its physicians with an automated clinical document improvement (CDI) solution to improve electronic healthcare records (EHR) and to ensure quality patient outcomes. UHS sought an advanced documentation capture tool that could be easily integrated with its EHR system to assist physicians in real time with automated transcription and documentation while improving medical diagnosis.

Actions Taken: Nuance's healthcare NLP solution, a Computer-Assisted Physician Documentation (CAPD) tool, is powered by Dragon Medical One, Nuance's healthcare AI system. CAPD enables physicians to dictate progress notes, history of present illness, etc., while the AI transcribes these notes in real time using Nuance's cloud speech recognition system. Embedded into the UHS's EHR system, CAPD reportedly offers physicians real-time intelligence by automatically prompting them with clarifying questions while they are documenting. However, Dragon Medical One only asks clarifying questions in specific circumstances, such as possibilities of a different diagnosis or piece of medical information that the physician should consider (i.e. when such clarifying questions are necessary). This CAPD tool is also integrated with the Cerner Document Quality Review (DQR) tool, which automatically determines the existence of clinical evidence that supports a more specific diagnosis.

Results: Nuance claimed that "UHS realized a 12 % increase in case of mixed index [which is a relative value used to determine resource allocation to treat patients in a particular diagnostic group] across the cases where physicians agreed with the CAPD clarifications, and updated their patients' documentation accordingly." Nuance also said its healthcare AI system improved UHS's identification of "extreme" cases of the severity of illness by 36% and the risk of mortality by 24%. UHS also reportedly achieved a 69% reduction in transcription costs year over year, resulting in $3 million in actual savings.

This case study highlights the advantages of AI in the field of food and agriculture. Note that the Nuance Communications solution adopted by United Healthcare Services (UHS) has not only solved the problem of medical data management and medical documentation but has also generated huge organizational benefits (financial, marketing and administrative performance). What we found interesting about this application with Nuance and UHS is the set of special features that make this use case interesting for UHS. Some interesting features of Nuance's solution (which will likely translate into other industries in the coming years) are as follows: (1) Find business problems where transcription costs (time and money) can already be measured and quantified. This addresses a specific and known business problem, which is essential to enter into agreements and encourage organizations to test a new software solution through a good planning and coordination process; (2) Encourage users to clarify their statements if necessary. It is important to record your thoughts, but it seems very useful to record all the ideas required and necessary to perform a task or process to choose solutions that effectively meet business needs (AI management capabilities). This case study provides evidence of support for the P1, P2, P3, P4, P6 hypotheses of the research.

6. Results and discussion

Based on the in-depth and detailed analysis of the case studies, it is clear that AI and its technologies offer a wide range of options, benefits and services, with the aim to improve organizational performance. Table A1 (Appendix 1) presents the benefits of implementing AI and its technologies across several business lines while identifying their business value to organizations. The deployment of AI in this regard has transformed the process into an intelligent, optimized, self-reactive, effective, efficient and automatic one, eliminating many processes that had previously been done manually, on paper and requiring significant resources. Due to its efficiency and quality in terms of innovation, AI deployment very often covers the entire value chain of the organization: research and development, maintenance, operation, sales/marketing, planning and production, demand forecasting and services. Our analyses reveal the vastness of AI's potential in organizations, such as (1) increment of the efficiency of operations, maintenance and supply chain operations; (2) optimization and improvement of the customer experience, products and services through new functionality, automation and optimization of sales and article recommendation processes; (3) improvement of rapid and automatic adaptation to changing market conditions, creation of new business models; (4) optimization of the relationship between supplies and needs with improved forecasting and planning capacity; (5) detection of fraud in the banking and other sectors; (6) automation of threat and IS monitoring and information systems; (7) diagnosis and diseases treatment, reduction of medical errors and improvement of the quality of patient care.

Of the 500 case studies we examined (Appendix 2, Table A2), nearly half (40.60%) of our sample were using pure AI. This type of AI refers here to the use of several types/technologies of AI. For example, it may be used to perform an analysis, automate tasks, support decision-making or redesign an organization's processes by integrating a digital (intelligent) transformation. Our analysis also revealed a strong propensity for organizations to use automatic learning. Almost one-third (31.20%) of our sample indicates its use in organizations. This attraction for automatic learning is explained by the fact that this type of AI technology minimizes human intervention in processes. Also, with this technology, the system becomes more and more intelligent as it learns. Thus, the more the machine (programs) is used, the more effective the system becomes, the more accurate and efficient its results are, and the less human intervention is required to make it work. We also noted that 18.60% of the organizations in our sample have adopted personal, virtual and robotic assistants to automate their production processes. Neural networks, although a popular technology in organizations is less present in our sample. This is probably because neural networks, which are generally very complex, are in most cases, developed and implemented by each organization. Our study refers to the use of AI in the field of safety (1.20%), cognitive safety. First, this low usage rate in our sample is primarily due to the fact that this AI technology requires many complementary resources and technologies, including different forms of AI (learning algorithms, learning networks), the cloud, and social networks. Second, it requires the collection of billions of data artifacts from structured and unstructured sources, as well as threat information contained in millions of research reports, blogs and news reports, etc. And finally, the complete case studies dealing with this type of AI in our study are only from IBM.

The in-depth analysis of the case studies also revealed the potential of AI to revolutionize all aspects of our daily lives. Almost all sectors of activity are concerned by this technology, which promises, through its innovative technologies, many advances (Appendix 1, Table A1). The technological sectors (IT/Telecom, electronics) are concerned by the current advances in AI technologies. In cybersecurity, AI's capabilities and technologies allow organizations to optimize their security devices. IT development organizations use AI in development and testing environments. "Machine Learning" allows Business Intelligence to acquire new tools to explore Big Data and automate recommendations. AI affects more sensitive areas where data is essential and vital to the proper functioning of the organization. This is the case for health and banking, where artificial vision, neurolinguistic programming, chatbots, automatic natural language processing and "Deep Learning" open up interesting perspectives. Our case studies focus on the security of data exchanges in these sectors of activity. The potential of AI has also been demonstrated in the manufacturing and construction industries—Machinery and Equipment, Aerospace, Rail and Shipbuilding, Construction Materials and Construction—where it automates budgeting and planning, as well as inventory and replenishment, increases workflow reliability and efficient use of resources, eliminates inaccurate and time-consuming processes, and improves the real-time visibility of assets, personnel and end-to-end supply chains.

In the logistics and transport sector, by explaining complex factors and correlations and eliminating intermediaries, AI assists organizations in predictive maintenance, improving user engagement. The main beneficiaries of AI's innovations are commerce, trade, distribution, communication, marketing and advertising. Indeed, personal virtual assistants, Machine Learning, emotional agents and chatbots are used in these areas to improve interactions, communication with customers. The fashion industries—textile, clothing, costume—use automatic learning to anticipate consumer habits or predict future trends, customize purchasing paths and optimize recommendation systems. Finally, AI is used in the education sector to create personalized and dynamic learning paths.

6.1 AI capabilities

The first thing that emerges from the case study analysis is that the successful deployment of AI in organizations requires three things: computing power infrastructure (high speed and infinitely scalable), algorithms (machine learning and/or deep learning, neural network), and rich data sets. These three elements constitute the essential elements of AI capabilities (AI Management Capabilities, AI Personal Expertise, AI Infrastructure Flexibility). These three concepts of AI capabilities are interdependent, as demonstrated by case studies.

Our case studies revealed that organizations have control over the first criterion: AI management capabilities. The other two criteria (AIPE, AIIF) are highly supplier-dependent in some case studies where managers have a rather vague idea of the business value of AI transformation projects in their organizations. Some suppliers such as IBM and CLOUDERA, provide organizations with AI expertise and an appropriate flexible infrastructure to optimize data processing and create added value for the organizations concerned. Also, we noted that most of the case studies presented an existing set of IT resources that were still not robust, unoptimized, insufficient and unnecessary for the successful deployment of AI. In most case studies, a combination of these resources with automated and intelligent processes, the control, coordination and planning of the organization's processes and resources has improved the quality of decisions and workflows. As for the expertise of AI staff, there are two main conclusions to be drawn from the quotes and lines drawn from the interviews. First, when AI solution providers deploy directly on site, there is close collaboration between the two organizations. This collaboration ranges from needs analysis to the modeling of intelligent processes using algorithms. Besides, organizations use suppliers to effectively develop, distribute, support and manage intelligent systems so as to change or disrupt their business environment and strategies, improve competitiveness, as well as their services and products. All this is done in partnership with AI solution providers, as AI skills are scarce. Second, when the organization works with an "AI as service" solution or an "AI as IaaS," its staff members do not benefit from the experience of the AI provider's technicians, because the organization's managers are more interested in the results. The organization's staff is only involved in expressing the need, describing the dimensions of the data used to feed the supplier's algorithms and using the solution. Finally, it emerges that all these capabilities can have major influences on processes, which, if well managed upstream by managers and leaders of organizations, can lead to high levels of organizational performance and to the achievement of business value from AI-based organizational transformation projects.

6.2 Process level

Indeed, our case studies revealed that the implementation of AI in organizations was intended to solve a single problem at the process level (improvement of automation, informational or transformational effects). With further analysis, it appeared that at the process level, organizations would want to solve problems such as the following: (1) re-engineer and redesign the existing organizational structure to improve customer relations; (2) automate processes and procedures; (3) take advantage of all types of data within and between organizations; (4) optimizing the collection, storage, processing and dissemination of information within and between organizations; (5) modify organizational processes to improve integration, cost reduction, business intelligence; (6) increase the efficiency of business processes; (7) foster the acquisition and assimilation of internal and external knowledge; (8) configure/reconfigure resources to align with the organization's vision. Information effects, in turn, influence administrative performance, as they allow organizations to obtain more information and make quick and high-quality decisions, and indirectly increase responsiveness and better management of their resources. The automation effects generated by AI capabilities in organizations are essentially the elimination of several redundant and centralized processes, the reduction of errors by staff, and the real-time visibility of internal and external resources. All these elements have considerably contributed to improving administrative and marketing performance through automation effects in terms of efficiency, reliability, and routinization of organizations' operational processes.

As an innovative and often disruptive technology, AI enables the design of new products, services, manufacturing or organizational processes directly implemented in the production system and meeting consumer needs. Thus, the transformational effects of AI's process capabilities are materialized in the case studies by re-engineering processes (some support functions are reduced to generate more value for customers), redesigning organizational structures by decentralizing basic decision-making by staff, customer satisfaction, and improving the quality of products and services. These thus contribute to better financial, marketing and administrative performance.

Although most of the previous research on AI has been limited to financial measures as a key indicator of organizational performance, our research also applies to administrative and marketing performance to highlight the direct and indirect influence of AI on organizational performance and also to show evidence related to the business value of AI transformation projects in organizations.

7. Limits and implications

7.1 Limitations

Case study research faces some limitations, as with any empirical research. The data collected within the framework of a case study are not spontaneous, but secondary. Also, case study data may have been inherited with missing data. Although the case studies provided a significant amount of information, there may have been an element of bias in the data contained in the cases, such as exaggerated claims or even restrictions on published data. We recommend combining several data collection tools such as interviews, questionnaires, secondary data analysis, and direct observation, in order to make cross-checks and obtain richer, more complete insights into our research question. A replica of this study, including fieldwork, observations, and interviews with organizations to document each of our case studies, may provide additional information and expand our understanding of the influence of AI on organizational performance.

This research work is a cross-sectional study that provides an overview of the survey at a given time. It does not consider longitudinal variations in AI and organizational capacity performance. A longitudinal study would examine the factors of AI capacity that influence organizational performance and estimate long-term productivity trends resulting from IT investments. Most studies did not have information on the cost and duration of implementing AI-based transformation projects. Evaluating the costs of these projects would allow organizations wishing to implement AI to act and control. In fact, it represents the best possible approach in economic terms to the valorization of a transformation effort between two states (from raw materials to the finished product). The duration of the projects would allow others to give an idea of how future AI transformation projects will unfold. Thus, based on this duration and other information in our case studies, organizations can establish an exhaustive list of tasks that would be sequenced to determine interdependencies and the order in which they should be carried out.

7.2 Managerial, theoretical and practical implications

Any organization needs a clear daily strategy to able to achieve its objectives. These are attained only when organizational managers mobilize the necessary human, technological or financial forces. Artificial Intelligence integrated into organizations will solve most problems by improving process performance (automated effects, informational effects, and transformational effects) and organizational performance (financial performance, marketing performance, and administrative performance). Not only does our study answer the question, "Can AI benefit my organization, and what can AI innovate?" but it will also allow a good number of organizations to solve their internal problems. In this regard, the following capabilities are necessary: mutualization (ability to identify a service provided by the organization and use it in several contexts); scalability (the ability of the organization to develop through a change of scale, i.e. to eliminate larger processing volumes without compromising the underlying architecture); and resilience (the ability of the organization to continue its activity in the event of a failure).

Analysis of our case studies showed that an organization having integrated AI with its operations and processes will have to be very likely managed in project mode, and will therefore need to undertake some actions regarding its adoption of AI Amongst others, the organization concerned should (1) prepare and train its leaders, collaborators and stakeholders to get acquainted of the specificities of AI transformation, so as to facilitate adoption; (2) guarantee the quality of future jobs in a context of human-machine interaction; (3) organize an internal and external "control tower" on ethical issues related to data and algorithms to ensure trust; (4) recruit and retain new talent needed for AI, anticipate changes in employment and skills, or even professional identities, in the company; (5) adapt training tools to cope with increased volumes and changes in training contents; (6) adapt its own governance to a new balance between centralization and decentralization of decisions; (7) accompany not only the new AI-induced operation modes, in particular with transversality and transparency, but also major changes in the role of managers at different levels. Contrary to previous researches in this particular field, this study has met the challenge of investigating at the same time the use of several AI technologies in several sectors of activity. It should be noted that previous studies have focused on AI technology in a particular sector of activity like Health, Automotive, or Banking. By conduct a holistic research exercise on various AI technologies as applied in more than one industry, we have pioneered research in this field. This combination of AI technologies is justified by the fact that most organizations in our sample do not need a single AI solution or technology, but a combination of these to achieve a greater benefit. The result obtained is important in practice and for organizational leaders and AI solution providers. Indeed, findings recommend that solution providers should emphasize on solutions that integrate a set of technologies rather than providing a single type of technology to organizations. Moreover, organizational managers should explore the benefits of using multiple AI technologies. In sum, this study reveals the polymorphic nature of AI, as it shows managers once again that they do not consider it as a single technology but as a set/combination of several different configurations of IT in the different fields of activity of their organization.

Our study has several theoretical implications for AICAP research to be considered in future research. First, it is one of the first studies to assess the direct impact of AICAP on firm performance, which significantly contribution to the research stream on the business value of IT as it confirms the importance of investing into AI personal expertise and AI infrastructure flexibility to boost the business value of AI transformation projects in organizations. Second, this paper adds to current studies that explore the business value of AI in organizations. To some extent, it can help pave the way for future research directions on innovation in services based on any AI technology.

8. Conclusion

The importance of AI becomes apparent as the contours of digital transformation become clearer. Organizations have become aware of the value of the data they have at their disposal. They now need tools to exploit them better. The emergence of AI is thus encouraged by a double movement: the digitization of the economy and the automation of existing processes, on the one hand, and a disruption in the supply of services based on the exploitation of this deposit on the other hand. In short, in this study, which focused on analyzing the influence of AI on organizational performance, we adopted a qualitative approach based on the analysis of 500 case studies. The choice of this approach was justified by the benefits it offers and by the fact that this type of research is based on secondary data (case studies). It allowed us to better capture and discover the meaning of the information in the case studies, to extract specific data for each organization, and finally to highlight the business value of AI transformation projects and expose the influence of AI on organizational and process performance. Thus, the qualitative analysis applied to the case studies resulted in the number of case studies that supported the proposals being presented in Table 2.

The use of AI is subject to contrasting judgments. On the one hand, this set of new techniques/technologies seems very promising for the future of organizations. On the other hand, its concrete applications still face many unresolved challenges. There are currently no regulations governing the functioning of AI and ensuring that it does not violate ethical rules (Dignum, 2018; Hooker and Kim Tae, 2019; Pwc, 2018). Besides, many organizations (IEEE, CERNA) have initiated discussions and published recommendations for researchers and developers to build intelligent, ethical systems (Davis John, 2005; Hooker and Kim Tae, 2019; Schweitzer and Puig-Verges, 2018). The question of the morality of their actions is beginning to arise. Those that rely on artificial neural networks (Deep Learning) are particularly criticized for being opaque, for not showing the reasoning that allows algorithms to arrive at the final result(Davis John, 2005; Hooker and Kim Tae, 2019; Schweitzer and Puig-Verges, 2018). But how can we trust decisions about AI if we are not able to understand them?.

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Appendix

Appendix 1. Common benefits of AI-enabled transformation projects

Industry	Common benefits of AI-enabled organizations transformation projects
IT/telecom	Improve the unstructured analysis of data capabilities for the existing solutions (IE, TE); Anticipate market evolutions (TE); Facilitate decision-making to strengthen competitive advantage (TE, AP); Provide a first-class experience that builds user loyalty (TE, MP); Provide customer service at a lower cost (MP)
Health	Improve medical care by analyzing a patient's data against relevant clinical data from around the world (TE, IE); Provide timely information that improves patient knowledge and the ability of health care providers to help (TE, IE); Significantly improve the speed of reading millions of databases, which now takes just a few seconds, instead of two years with manual processing (AE, TE, FP); Gain new customers and increase revenue with a real-time analysis solution (FP, AE); Improve the accuracy of clinical responses and queries (AE); Improve the ability of physicians/clinicians to treat and manage chronic diseases (AP, TE)
Bank	Automate transactions by quadrupling the number of transactions processed per month from 2 million to 8 million (EI, TE); Estimated revenue growth of more than 10% since adoption (FP); Expand financial services customer base (TE, FP); Support customer acquisition by focusing on new digital services (TE, MP); Reduce delays for the deployment of new mobile applications (FP) by 40%; Foster innovation by limiting software costs through a corporate license agreement (FP, TE); Improve customer experience (MP); Reduce operating costs by 80% through a wide range of customer services and operational improvements (FP, TE); Reduce customer service costs while increasing revenue through better service (FP, MP); Detect and combat fraud and money laundering (TE)
Sales/trade/distribution	Accelerate the process of collecting and analyzing social media data(TE, AE); Provide the best coverage in the social media world, with a broader range of data sources (TE, AP); Help make products easier to discover on social media (TE); Allow customers to automate the collection and preservation of user-generated social content in the pipeline (TE); Connect the customer to the right products in the catalog (TE, MP); Match images with products to recommend to buyers (TE, MP); Save time, improve accuracy and help consumers to find things easily without wasting time (MP, AP); Allow organizations to streamline the development of their models from start to finish without sacrificing training speed (AP)
Transport and logistics	Increase by 146% the number of direct bookings (FP); Improve user engagement by providing a more personal experience (MP); Optimize Supply Chain and Production (TE, AP); Predictive and autonomous maintenance (AP); increase revenue by getting more commissions with more bookings (FP); Improve travel experience and visibility; Reduce problem resolution times by 90% by simplifying data discovery and uncovering root causes (TE, IE); Reduce delays, cancellations leading to greater customer satisfaction and operational efficiency (MP, TE); Reduce decision- making time by finding solutions to complex problems without manual research and analysis (AP) processes; Reduce costs by allowing increased asset utilization, as 24/7 executions are possible (MP, AP)

(*continued*)

Table A1.
Summary of the benefits realized from the capabilities of AI and its derivatives in several sectors of activity

Industry	Common benefits of AI-enabled organizations transformation projects
Education	Increase the graduation rate (TE); increase the recruitment of undergraduate and graduate students through a more sophisticated recruitment program (AP, TE); Optimize the alignment between the curriculum and the demand for workplace skills (TE, AP); Strengthen collaboration and partnerships between the institute's academic staff and the business community (AP); Provide analytical skills on demand to more students than ever before (AP, TE); Encourage students to work independently and find solutions to real-world problems (AP, TE); Prepare students for post-graduate life in employment or further studies (AP)
Insurance	Unlock faster insight into information to make timely decisions (IE); Enable business users to better control their data with self-service features (AP); Free up the business intelligence team to focus on more strategic analysis work (AP, FP); Reduce claims by helping customers protect their property from damage caused by bad weather (AP, MP); Classify and associate with contextual information (AE, IE); Help analysts to focus on their core tasks (AP); Encourage the adoption of mobile insurance applications, for more responsive and less expensive customer service (MP); Promote loyalty and help reduce churn by stimulating customer engagement (MP, FP)
Automobile	Eliminate erroneous and time-consuming processes (AE, FP); Automate manual and paper-based processes that reduce waiting times (AE, FP); Improve real-time visibility of assets, personnel and end-to-end supply chains (AP, IE); Assist organizations in complying with regulations and policies (AP); Improve increased staff productivity and reduced staff requirements (AP, FP); Automate inventory and replenishment (AE); increase workflow reliability and efficient use of resources (AP, IE); Help overcome financial losses (FP); Improve the quality of decisions in organizations (IE); Automate budgeting and planning (FP); increase financial profits and returns on investment faster in a few months (FP); Provide greater control over management processes and planning (IE, AP)
Computer services	Enhance the unstructured data analysis capabilities of its existing solutions (TE); Empower customers to anticipate market changes and make decisions to sharpen their competitive edge (TE, IE, MP); Free developers to do their best work and build a great app (AP, IE); Top-notch experience keeps users engaged and helps Campus Discounts grow (MP, FP); Innovative cognitive capabilities make it even easier for students to find deals (TE, AP)
Aerospace and defense	Improve user efficiency when troubleshooting issues (MP, AP); Expect to reduce the time needed to solve contextual issues using the knowledgebase of the new solution (AP, TE); Expect to reduce the risk of missing a flight connection or having a connection get canceled (AP, TE); Expect to improve the quality and the safety of aircraft travel and maintenance (AP)
Business services /professional services	14+ violent acts against schools pre-empted by Tactical Institute's vigilance (AP); 500m + new social media posts analyzed per day by threat analytics (AE); Accelerate the way to collect and analyze social media data (AE); increase the chances of detecting threats and alerting security or law enforcement in time to intervene (AP, TE); Give the better coverage of the social media world, with a wider range of data sources (IE, TE); Give a sharper view of the context of individual messages (IE); increase productivity for its customers (MP)
Government	10+ asset and service management systems retired, thus reducing complexity (AP); Single point of control for asset management (AP); Data-driven insights support operational planning (IE); Reduce costs in the customer care organization by resolving routine inquiries without human intervention (MP, FP); Speed response times and minimizes backlogs in email, live chat and phone queues (TE, AE, MP); Boost satisfaction and improves the visitor experience, encouraging repeat visits (MP)

(*continued*)

Table A1.

Industry	Common benefits of AI-enabled organizations transformation projects
Ecommerce	Help to make products more discoverable on social media (MP); Allow customers to automate the collection and curation of user-generated social content in the pipeline (TE); Connect the customer to the right products in the catalog(MP); Match images with products to recommend to shoppers (MP); Save time, improve accuracy, and help consumers find things easily without wasting time(MP, FP); Allow the organization to streamline their end-to-end model development without sacrificing training speed (TE)
Financial markets / financial services	Quadruple the number of transactions processed per month, from 2 million to 8 million (FP); 10% estimated revenue growth since adopting (FP); Expand customer base into the financial services sector (FP); Improved customer experience (MP); 80% reduction in operating costs through a wide range of customer service and operational improvements (FP); decrease in cost to service customers while increasing revenue through better service (MP, FP)
Chemicals and petroleum	Increase delivery speed and consistency of reservoir rock sample descriptions (TE, IE); Accelerate model construction to de-risk multibillion-dollar reservoir development decisions (AE, TE, IE); Preserve expertise that petrographers have spent decades developing (AP); 10M savings in employee costs (FP); 75% reduction in time spent by the geoscience team in reading and searching through data sources (FP, AP, AE); Accelerate expertise by giving staff unlimited access to 30 years of tribal knowledge; Faster access to and more intuitive analysis of engineering records (AE, AP)
Technology	Speed up object detection and deliver pertinent results in real time (AE); save over 90% of their costs(FP); Make it more economically feasible to service the volume of requests they receive daily (FP)

Table A1.

Appendix 2. Organization's business line and types of technologies of AI

Industry (number of cases/ percentage)	Types of AI
(1) IT/telecom/computer services (74/ 14.80%); Health (42/ 8.40%)	(1) AI strong or weak (206 /41.2%)
(2) Bank/ financial markets / financial services (39/ 7.80%)	(2) Machine leaning (157/ 31.4%)
(3) Business services /professional services (38/ 7.60%)	(3) Deep learning (13/ 2.6%)
(4) Trade/Trade/Distribution (37/ 7.40%); Automobile (36/ 7.20%); Machinery and equipment (27/ 5.40%)	(4) Cognitive (65/ 13%)
(5) Audiovisual, Show (24/ 4.80%); Electronics (20/ 4.00%); Other(19/ 3.80%); Metallurgy/Metalworking(19/ 3.80%)	(5) Cognitive cyber security (6/ 1.2%)
(6) Insurance (13/ 2.60%); Research (11/ 2.20%); Plastic/ Rubber (11/ 2.20%)	(6) Natural language processing /Understanding (69/ 13.8%)
(7) Logistics and transport (10/ 2.00%); Education (10/ 2.00%)	(7) Robotic personal assistant (93/ 18.6%)
(8) Pharmaceutical industry (6/1.20%); Aircraft, rail and shipbuilding (4/ 0.80%)	(8) Pattern/visual recognition (10/ 2%)
(9) Petroleum industry (3/ 0.60%); Ecommerce (2/ 0.4%); Aerospace and defense (3/ 0.60%)	(9) Chatbots (38 / 7.6%)
(10) Textile/clothing/headwear (3/ 0.60%); Army, security (3/ 0.60%); social (2/ 0.40%); Construction / building materials (2/ 0.40%)	(10) Neural networks (4/ 0.8%)
(11) Art, design (2/ 0.40%); Studies and advice (1/ 0.20%); Hotels, restaurants and catering (1/ 0.20%)	(11) Virtual companion /virtual assistant (39/ 7.8%)
(12) Tourism, Leisure activities (1/ 0.20%); Government (9/ 1.80%); Agri-food industry (9/ 1.80%); Agriculture (9/ 1.80%); Energy (6/ 1.20%); Communication - marketing – advertising (4/ 0.80%)	(12) Real TIME emotion analytics (5/ 1%)
	(13) Real Time universal translation (6/ 1.2%)
	(14) Next GEN cloud robotics (3/ 0.6%)
	(15) Autonomous surgical robotics (3/ 0.6%)
	(16) Virtual reality (12/ 2.4%)

Table A2. Organization's business line and types of technologies of AI

Appendix 3. List of suppliers from whom case studies were collected for this research, followed by the Case Study Links in our sample

AI providers	Url
IBM	https://www.ibm.com/watson/ai-stories/, https://www.ibm.com/services/artificial-intelligence
AMAZON	https://aws.amazon.com/fr/solutions/case-studies/all/, *https://aws.amazon.com/fr/blogs/machine-learning/*
Cloudera	*https://www.cloudera.com/about/customers.html*
Conversica	https://www.conversica.com/resources/customer-stories/, *https://www.conversica.com/resources/case-studies/*
Logz.io	*https://logz.io/case-studies/*
Microsoft	*https://customers.microsoft.com/fr-fr/story*
Cognitivescale	*https://www.cognitivescale.com/case-studies/*
Universal robots	*https://www.universal-robots.com/case-stories/*
Others	https://emerj.com/ai-sector-overviews/5-business-intelligence-analytics-case-studies-across-industry/, https://www.nvidia.com/fr-fr/deep-learning-ai/customer-stories/, *https://www.tamr.com/case-study/* , https://www.cnbc.com/2016/10/24/bank-of-america-launches-ai-chatbot-erica–heres-what-it-does.html, https://www.bbva.com/en/bbva-customers-can-use-voice-and-chatbots-send-money-other-smartphones/, https://www.cnbc.com/2016/10/24/bank-of-america-launches-ai-chatbot-erica–heres-what-it-does.html, https://customers.microsoft.com/fr-fr/story, https://dxilogy.com/site/wp-content/uploads/DXI_CaseStudes.pdf, https://aws.amazon.com/blogs/machine-learning/thorn-partners-with-amazon-rekognition-to-help-fight-child-sexual-abuse-and-trafficking/ https://aws.amazon.com/fr/partners/apn-journal/all/, http://www.channelpostmea.com/wp-content/uploads/2017/12/Neuromem-product-case-study_manansuri_updated_final.docx, https://www.linksquares.com/customer-snapshots/kensho, https://aws.amazon.com/fr/solutions/case-studies/, https://asana.com/fr/case-study, https://blog.asana.com/2017/09/invision-process-execute-great-marketing-campaigns/, https://blog.akilahinstitute.org/empowering-women-withasana-8ee1ca7ffd98, https://www.smartaction.ai/blog/electrolux-call-automation-virtual-agents/, https://www.retaildive.com/news/ibm-watson-to-power-staples-easy-button/429094/ https://emerj.com/ai-sector-overviews/7-chatbot-use-cases-that-actually-work/, https://resources.conversica.com/i/851737, https://marketing.optis-world.com/acton/ppform/17674/000d https://www.optis-world.com/fr/Nos-R%C3%A9alisations/Success-story/Quintessence-Yachts, https://www.daisyintelligence.com/case-studies/, https://qventus.com/

Table A3. List of suppliers from which case studies were collected for this research

About the authors

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